USING SUBJECTIVE EXPECTATIONS TO FORECAST LONGEVITY: DO SURVEY RESPONDENTS KNOW SOMETHING WE DON'T KNOW?*

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Old-age mortality is notoriously difficult to predict because it requires not only an understanding of the process of senescence—which is influenced by genetic, environmental, and behavioral factors—but also a prediction of how these factors will evolve. In this paper, I argue that individuals are uniquely qualified to predict their own mortality based on their own genetic background, as well as environmental and behavioral risk factors that are often known only to the individual. Given this private information, individuals form expectations about survival probabilities that may provide additional information to demographers and policymakers in their challenge to predict mortality. From expectations data from the 1992 Health and Retirement Study (HRS), I construct subjective, cohort life tables that are shown to predict the unusual direction of revisions to U.S. life expectancy by gender between 1992 and 2004: that is, for these cohorts, the Social Security Actuary (SSA) raised male life expectancy in 2004 and at the same lowered female life expectancy, narrowing the gender gap in longevity by 25% over this period. Further, although the subjective life expectancies for men appear to be roughly in line with the 2004 life tables, the subjective expectations of women suggest that female life expectancies estimated by the SSA might still be on the high side.

The twentieth century witnessed unprecedented improvements in life expectancy. In the United States, life expectancy at birth rose from 47 years in 1900 to 77 years in 2000 (National Center for Health Statistics 2004).[1] Although most demographers agree that mortality rates will continue to decline in the twenty-first century, there is little consensus on how fast and for how long they will continue to fall (e.g., Lee 2003; Vaupel and Lundstrom 1994). The answers to these questions are at the heart of some of the most important issues in the economics of aging, including income adequacy in retirement and the solvency of the social security system.

Many mortality forecasts are based on extrapolations of historical data. However, extrapolating historical trends may be misleading. For example, simple extrapolative procedures fail to incorporate information about potential changes in the factors underlying mortality hazards over time. This paper provides a somewhat unorthodox alternative to using historical data to project the path of mortality risk. The method proposed here uses data on individual, subjective expectations of survival to construct subjective life tables for a particular cohort. This method has an important advantage over extrapolative methods in that subjective expectations incorporate current and future expected values of variables that influence mortality risk, such as exercise, diet, and smoking habits. Because much of this information is private, individuals are uniquely qualified to assess how these factors will influence their personal mortality risk, which is a function of their medical history, current health status, and family history. By aggregating these individual forecasts of mortality risk across persons in a given cohort, one can obtain a subjective, cohort life table that incorporates causal mechanisms implicitly and does not explicitly depend upon historical trends.

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1. Cutler and Meara (2004) provide an excellent overview of the causes underlying mortality improvements during the twentieth century.

The purpose of this paper is to explore the mortality forecasts implied by the subjective expectations of a cohort of individuals in the Health and Retirement Study (HRS) in 1992. There are three main findings. First, subjective life tables differ significantly from life tables put together by the Social Security Actuary (SSA) in 1992, and the deviations from the life table differ significantly by gender. In particular, subjective life expectancies estimated for men are higher than the SSA life tables predict, and the subjective life expectancies for women are a good bit lower. Second, these subjective life tables suggest a further narrowing of the gender gap in longevity in coming decades, with men living longer and women dying earlier than predicted by the SSA. Part of this narrowing has already been reflected in revisions to the SSA life tables published in 2004 compared with those published in 1992, in which male life expectancies were revised upward and female life expectancies were revised downward. In essence, the subjective expectations data from 1992 predicted the direction of revisions to the SSA life tables between 1992 and 2004. The subjective expectations data also suggest a further narrowing of the gender gap in longevity for these cohorts that is not yet reflected in the SSA life tables. Finally, I demonstrate that the validity of the subjective survivor functions depends crucially on the functional form that governs changes in mortality after age 85. I show that different functional forms result in significantly different life expectancies, largely stemming from the shape of the survivor function beyond age 85. Nevertheless, I argue that the main findings of the paper are robust to these assumptions.

The paper proceeds as follows. The second section describes the unique expectations data available in the HRS. The third section demonstrates how these data can be used to construct individual-specific survivor functions, which are then aggregated by using population weights for a cohort of men and women in the HRS. The fourth section discusses the resulting subjective life tables and compares their mortality predictions with the life tables produced by the SSA in 1992 and then again in 2004. The final section offers concluding remarks and directions for future research.

THE HEALTH AND RETIREMENT STUDY

The data used in this analysis are from the first wave of the HRS. Initial interviews, conducted in 1992 and 1993, provide detailed information on the health status and socioeconomic status of a nationally representative sample of noninstitutionalized persons born between 1931 and 1941 and their spouses.[2] A total of 12,652 individuals were included in the final HRS sample in 1992. Variables of particular importance for this paper include subjective expectations of survival to age 75 and age 85, as well as indicators of the age and sex of the respondent.

This paper uses the HRS data on survival expectations to generate sequences of survival probabilities for each individual in the sample. In particular, respondents were asked to answer the following questions:

> I would like to ask you about the chance that various events will happen in the future. Using any number from zero to ten, where zero equals *absolutely no chance* and 10 equals *absolutely certain*, what do you think are the chances that you will live to be 75 or more? And how about the chances that you will live to be 85 or more?

The responses to these questions provide an indicator of survival expectations for HRS respondents, but it is not immediately obvious that they should be interpreted as cardinal measures, nor whether they provide information only on the ranking of outcomes. Hurd and McGarry (1995) suggested that when divided by 10, the responses can be treated as probabilities, which are hereafter referred to as P_{75} and P_{85}. In particular, Hurd and McGarry (1995) showed that, for the most part, the subjective survival probabilities are internally

2. Detailed documentation of the HRS is available in Juster and Suzman (1995).

consistent: the probability of living to age 75 is greater than or equal to the probability of living to age 85. They also demonstrated that the subjective probabilities covary in reasonable ways with other variables (such as health status) and that they are, on average, in the ballpark of the 1990 life-table probabilities.

Although previous work generally validated the interpretation of subjective expectations of mortality risk as survival probabilities, several features of the data are important to note. First, as noted in Hurd and McGarry (1995), about 2% of the sample reported greater probabilities of living to age 85 than of living to 75. Clearly, these individuals either misunderstood the question or were unable to form internally consistent probabilities of survival. Whatever the reason, I cannot estimate survivor functions with internally inconsistent data; as a result, I drop these observations from the analysis.[3]

Another feature of these expectations data, also discussed by Hurd and McGarry (1995), is that responses tend to cluster around "focal responses" of 0, .5, and 1. In addition, a significant minority report the same probability for both P_{75} and P_{85}. A possible explanation for both of these phenomena is the coarseness of the 0- to 10-point scale for the responses in Wave 1, which forces individuals to round to the nearest tenth in probability terms. If this explanation were important, one should see much less clustering at focal responses and fewer reports of $P_{75} = P_{85}$ when the scale is expanded from 11 points in Wave 1 to 101 points for these same expectations questions in Wave 2. However, the prevalence of clustering appears to be very similar in Wave 2 despite the finer scale, and there is only a relatively small reduction in the percentage of the sample reporting the same value for P_{75} and P_{85} (e.g., from 23.3% to 16.5% for men). Hence, the tendency to report focal responses or the same value for P_{75} and P_{85} probably has more to do with uncertainty than reporting constraints, and it is possible that at least some of the values reported as "focal responses" are legitimate estimates of the probability measured with error. Indeed, the respondents that report $P_{75} = P_{85}$ may be conveying important information about the likelihood of survival to the age range between ages 75 and 85—which, for these respondents, is about 20 and 30 years ahead, respectively—and may well reflect a perceived flatness of the survivor function for these individuals over that range. Strictly speaking, estimating a survivor function is difficult with no reported hazard of dying within a 10-year period. However, given that these responses represent over one-fourth of the sample, and that they likely contain valuable information about survival expectations, persons who report the same value for P_{75} and P_{85} are retained in the sample, but their reported probabilities are altered somewhat to estimate the parameters of the survivor functions.[4]

Hurd and McGarry (2002) also demonstrated that subjective survival probabilities have predictive validity; that is, respondents who survived between Waves 1 and 2 of the HRS reported significantly higher probabilities of survival in 1992 than those who died.[5] This study noted that relative to the 1992 life tables, men tended to overestimate their survival probabilities, and women tended to underestimate them. They offered two potential explanations. First, because the HRS sample represents only the noninstitutionalized population and because men in this cohort are more likely to be institutionalized than women, the remaining sample of men would be healthier relative to the women. Second, the period life tables used in their analysis did not incorporate expected improvements in health that the men might experience and factor into their subjective survival probabilities. I expand upon

3. Appendix A provides further discussion of related issues.

4. For practical reasons documented in Appendix A, the subjective expectations data are adjusted for respondents who report $P_{75} = P_{85}$, as well as for respondents who report survival probabilities of 0 or 1. Alternative estimates, using unadjusted data, are also discussed in Appendix A.

5. More generally, there is an interesting literature on the validity and interpretation of subjective expectations data (e.g., Bassett and Lumsdaine 2001; Bernheim 1989, 1990; Dominitz 1998; Dominitz and Manski 1997; Hamermesh 1985; Manski 1990). Manski (2004) provided a particularly useful overview and discussion of the issues surrounding economists' use of subjective expectations data.

the Hurd and McGarry (2002) study by further exploring the gender-specific divergence in the subjective expectations data from the HRS and the life-table estimates published in 1992, with a particular focus on whether the subjective expectations contain information not yet incorporated into the 1992 cohort life tables published by SSA when the expectations were elicited. In fact, I find that the unusual direction of subsequent revisions to the cohort life tables published in 2004 moved the SSA life table into closer alignment with the subjective, cohort life tables that I construct by using the HRS. Although this closer alignment could be purely coincidental, the fact that the revisions were not uniform by gender is consistent with the idea that the subjective expectations data contain some information not previously incorporated into official life tables.

For this analysis, I focus on men and women aged 52 and 57 at the time of the first wave of the HRS. I choose these two age groups because the birth-year cohort life tables published by the SSA in 1992 and in 2004 are readily available only for birth-cohort years ending in 0 and 5.[6] Hence, among the HRS cohort, ages 52 and 57 align best with the available birth-cohort life-table data for 1940 and 1935, respectively. I drop about 2.5% of the observations because they reported subjective probabilities that were not internally consistent: that is, the subjective probability of living to 85 was strictly greater than the subjective probability of living to age 75.

USING EXPECTATIONS DATA TO PREDICT MORTALITY

The goal of this paper is to construct cohort life tables for men and women that are based primarily on subjective expectations of survival. A cohort life table describes the mortality experience of a cohort normalized to 100,000 births at age 0, giving the probability of death q_x between integral ages x and $x + 1$. Given q_x, all other life-table functions can be derived, including the number of individuals surviving to any exact age x (denoted by l_x) as well as life expectancy, or the average number of years remaining conditional on reaching age x (denoted by e_x).

Because the cohort life table is designed to reflect the mortality experience of a given birth cohort, forecasts of mortality rates will be required if the historical data are not yet complete, as is true for the cohorts born in 1935 and 1940. The life tables produced by the SSA describe their methods for projecting mortality experience for these cohorts (Bell, Wade, and Goss 1992).

Constructing Individual Subjective Survivor Functions

This section describes how the subjective expectations data from the HRS can be used to generate a sequence of subjective survival probabilities—or a subjective survivor function—for each individual in the sample. The basic method proposed here involves fitting a survivor function through the points P_{75} and P_{85} on the subjective survivor function. Note that this method is very different in spirit from an alternative method proposed by Gan, Hurd, and McFadden (2003) that used a Bayesian update model to construct individual subjective survivor functions.[7]

For the purposes of this paper, I maintain the assumption that the individual survivor functions can be approximated by a particular functional form. Two functional forms are commonly used in survival analysis: the Weibull distribution and the Gompertz distribution.

6. Subjective life tables were also calculated for those aged 51 to 61 at the time of the initial HRS interview. Although not shown here, comparison of the aggregate subjective survivor function for these 11 age cohorts with the life-table estimates from 1992 and 2004 yield similar qualitative results to those presented here for the age-52 and age-57 cohorts.

7. Gan, Hurd, and McFadden (2003) used data from the Asset and Health Dynamics of the Oldest-Old (AHEAD), which is representative of the population age 70 and older, to estimate individual-specific survivor functions. As a result, a direct comparison of the mortality forecasts from the different methods for a constant cohort are unavailable.

The Weibull distribution has been used extensively to model the lifetimes of manufactured goods as well as the lifetimes of insects, animals, and people (Lawless 1982). The popularity of the Weibull distribution in survival analysis owes, in part, to its flexibility in allowing decreasing or increasing hazard functions. Another attractive feature of the Weibull distribution is that the mean and variance have closed-form solutions (Lawless 1982).

The Gompertz distribution has been popular among demographers because its double exponential form has been thought to reflect the underlying process of aging that leads to death. Despite studies showing that the Gompertz model may not accurately characterize mortality risk among the oldest-old—that is, mortality hazards do not appear to continue to increase at the same exponential rate among the oldest-old—this distribution is still widely used and accepted (Economos 1982; Wilson 1994). The Weibull and Gompertz distributions each have two parameters, implying that they are exactly identified given two points on the survivor function, P_{75} and P_{85}. However, when P_{75} is sufficiently close to P_{85}, the exactly identified survivor functions are implausibly flat, yielding unreasonably high probabilities of survival in old age for a significant fraction of the sample. To induce the estimated survival probabilities to be close to zero in extreme old age, I introduce a third point on the subjective survivor function to which most respondents would not likely object. In particular, I set the probability of living to age 110 near zero, according to the simple conditional probability

$$P_i(110 \mid age_i) = \underbrace{P_x(110 \mid 85, age_i)}_{\text{SSA life table}} \times \underbrace{P_i(85 \mid age_i)}_{\text{HRS}},$$

where the first term on the right-hand side is the probability of surviving to age 110 given that a person survives to age 85 for $x \in \{male, female\}$. This term is calculated separately for men and women from the SSA cohort life tables (Bell, Wade, and Goss 1992). The second term represents the subjective probability of living to age 85 given that the respondent is age_i in 1992 (P_{85}).

The general strategy of this methodology is to estimate the parameters of the survivor function given P_{75}, P_{85}, and P_{110}, using nonlinear least squares (NLLS). In particular, I assume that

$$P_{i,t} = S_{i,t}(\alpha_i,\beta_i) + \varepsilon_{i,t},$$

where $P_{i,t}$ is the probability that individual i lives to age t, and $S_{i,t}$ is a general representation of a two-parameter survivor function. The error term $\varepsilon_{i,t}$ is assumed to be independent and identically distributed, with a mean of zero, and homoskedastic. The NLLS estimators are the values of α_i and β_i that minimize the following expression:

$$\Sigma_{t \in \{75,85,110\}} [P_{i,t} - S_{i,t}(\alpha_i,\beta_i)]^2.$$

Two sets of parameter estimates are calculated, the first under the assumption that the survivor function takes the form of the Weibull survivor function (α_i^W,β_i^W), which is given by

$$S_{i,t}^W(\alpha_i^W,\beta_i^W) = \exp\left[-\left(\frac{t-age_i}{\alpha_i^W}\right)^{\beta_i^W}\right],$$

and the second under the assumption that it takes the form of the Gompertz survivor function, which is defined as

$$S_{i,t}^G\left(\alpha_i^G,\beta_i^G\right) = \exp\left[\frac{\alpha_i^G}{\beta_i^G}\left(1-\exp\left(\beta_i^G\left(t-age_i\right)\right)\right)\right].$$

This estimation procedure assumes that each individual faces a unique sequence of survival probabilities that are generated from an individual-specific Weibull (Gompertz) survivor function. Further, each individual reports his or her survival probabilities with error. Under these assumptions, NLLS will provide unbiased and efficient estimates of the underlying parameters of the survivor function for each individual. As I show in the next section, an aggregate life table can be computed by applying population weights to the individual survivor functions.[8]

Constructing Subjective Cohort Life Tables

I use the two sets of NLLS estimates to generate a series of subjective survival probabilities—a Weibull and a Gompertz—for each person in the sample. To generate a representative, cohort life table, these subjective probabilities are multiplied by the HRS person-level weight and summed for each age-gender group. That is, the N sample members who are age X in 1992 (the age-X_{1992} cohort) represent a total population cohort of $\sum_{i=0}^{N} W_i$ persons, or the sum of the person-level weights (W_i), in 1992. Going forward, the number of persons from the age-X_{1992} cohort expected to be alive at age $X + t$ is given by $\sum_{i=0}^{N} W_i S_{i,t}$. This calculation gives the number of persons in the age-X_{1992} cohort that are expected to be alive at every age $x > X_{1992}$—or, in nomenclature of the life tables, l_x. After I obtain l_x for each age x, I can deduce all other life-table functions as follows:

$$d_x = l_x - l_{x+1}$$

$$q_x = \frac{d_x}{l_x}$$

$$L_x = \frac{l_x + l_{x+1}}{2}$$

$$T_x = \sum_{t=0}^{\omega} L_{x+t}$$

$$e_x = \frac{T_x}{l_x}.$$

Conceptually, the probability of dying between age x and age $x + 1$, q_x, is simply a count of the number of persons who die between those ages, d_x, divided by the number of persons alive at age x, l_x. Note that this function explicitly accounts for the selection of healthier individuals into older age groups because persons with higher mortality risk are more likely to die at younger ages; therefore, they are less likely to be included in the denominator l_x as x increases.

As is customary, these estimates assume that deaths are distributed uniformly over the year so that the average number of persons alive between time t and $t + 1$ is equal to L_x, which is the midpoint of l_x and l_{x+1}. The sum of L_{x+t} from $t = 0$ to ω, where ω is the maximum possible age, gives the total number of person-years lived by the cohort over its lifetime (T_x). Life expectancy is derived by dividing the total number of person-years lived by the cohort (T_x) by the total number of people alive at $t = 0$ (l_x).[9]

8. Alternatively, if one assumes that each individual in a given age-sex cohort actually faced the same Weibull survivor function and reported those probabilities with error, one could estimate the parameters of the aggregate survivor function by weighted NLLS on the entire cohort. Estimates of aggregate Weibull parameters using this method yielded life expectancies that were a bit higher for the 1940 cohort, but the main results of this paper still hold. Given the variation in risk factors and responses regarding expectations of survival, I maintain the assumption that each individual faces a person-specific survivor function, and I construct the life tables accordingly.

9. These basic life-table functions are described in more detail in Pollard, Yusuf, and Pollard (1990).

Table 1. Subjective Life Tables Versus Cohort Life Tables (SSA): Men Aged 52 in 1992

	Subjective Life Tables				1940 Cohort Life Table			
	Weibull[a]		Gompertz		Published in 1992		Published in 2004	
Age	Survival Probability S_x	Life Expectancy e_x	Survival Probability S_x	Life Expectancy e_x	Survival Probability S_x	Life Expectancy e_x	Survival Probability S_x	Life Expectancy e_x
52	1	28.2	1	26.5	1	25.9	1	26.7
55	0.976	25.9	0.946	24.9	0.976	23.5	0.977	24.3
65	0.848	18.9	0.773	19.4	0.853	16.1	0.86	16.8
75	0.647	13.2	0.589	13.9	0.618	10.1	0.647	10.6
85	0.366	9.3	0.378	8.8	0.287	6.0	0.332	5.7
95	0.146	6.6	0.153	4.4	0.053	3.5	0.053	3.0
105	0.029	6.0	0.008	1.5	0.002	2.2	0.001	1.9
115	0.006	6.3	0	1.0	0	1.3	0	1.1

[a]Weibull survivor functions are truncated at age 127 (i.e., $q_{127} = 1$). The truncation does not significantly affect life expectancy estimates before age 105.

RESULTS

Men

Although life tables could be constructed for all age cohorts, this paper presents selected life-table functions only for the age cohorts that align most closely with the 1940 and 1935 cohort life tables published in 1992: that is, men and women aged 52 and 57 in 1992,[10] respectively.[11] Table 1 presents the survival probabilities derived from the Weibull and Gompertz distributions for men aged 52; for comparison, the table also shows the life-table estimates that were published by SSA in 1992 and 2004. The table shows that the Gompertz survivor function is quite a bit flatter than the Weibull.

As illustrated in Figure 1, the Gompertz survival probabilities are significantly lower than the Weibull probabilities through about age 80, and then a bit higher through age 95, before dropping much faster after age 95. It appears that the survival probabilities from the Gompertz survivor function are too low at younger ages, perhaps indicating that the Gompertz distribution is not appropriate. Indeed, Wilson (1994) noted that for human survivor functions, there appears to be a shift in the exponential parameter at older ages; that is, mortality does not increase at the same exponential factor over the entire length of life, and it likely decelerates in old age.[12]

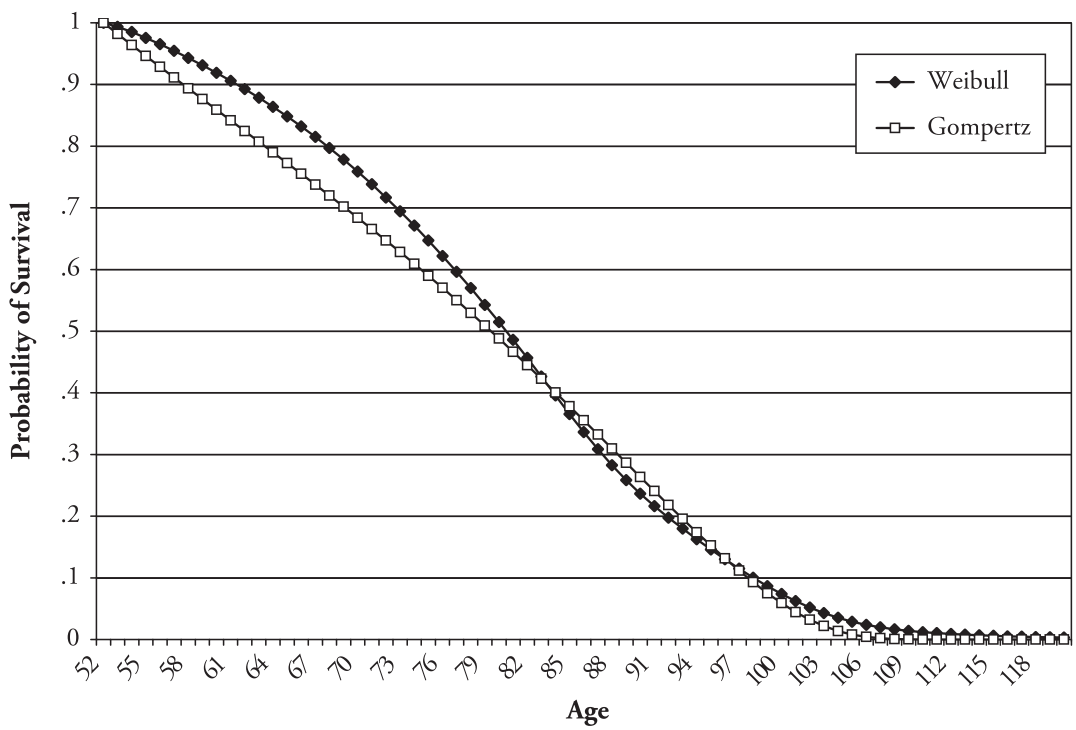
Not surprisingly, life expectancy is higher in the subjective cohort life table derived from the Weibull relative to that derived from the Gompertz: the Weibull estimate of life expectancy at age 52 is 28.2 years, and the Gompertz life expectancy is 26.5 years. Table 1 shows that these Gompertz and Weibull life expectancy estimates are between 0.6 years and 2.3 years higher, respectively, than the life expectancy of 25.9 years published in the 1940 cohort life table from 1992—the year when these subjective expectations data were gathered. If these subjective life tables had been taken seriously in 1992, they may have suggested that the life expectancy estimates for this cohort were too low. Indeed, as shown

10. Hereafter, I will refer to the Wave 1 interview year as 1992 even though a small number of Wave 1 interviews were conducted in 1993.

11. Complete, subjective cohort life tables are available from the author upon request.

12. Vaupel et al. (2004) investigated the possibility that mortality rates actually decline beyond a certain age, a phenomenon that they termed *negative senescence*.

Figure 1. Subjective Survivor Functions for Men Aged 52



in the top row of the right-hand columns of Table 1, the SSA revised upward its estimate of life expectancy for this cohort by a significant margin of 0.8 years when it reestimated the 1940 cohort life table in 2004.

The revision to the life-table estimates are shown in more detail in Figure 2, which compares the survivor functions from the SSA life tables published in 1992 and 2004 with the Weibull subjective survivor function. The results show that the revisions to the 1940 cohort life table in 2004 pushed the survival probabilities from the cohort life table into closer alignment with the subjective survivor function at almost every age up through the early 90s. Moreover, the figure shows that the Weibull estimates track the 2004 life-table estimates almost exactly up through age 80, at which point the subjective survivor function diverges from the SSA life table. In particular, the Weibull survivor function has a much fatter right tail, implying that the probability of surviving to older ages is a good bit higher than what current life-table estimates predict. As I discuss later in this paper, the key to estimating life expectancy for this age group lies in the assumptions underlying mortality forecasts at ages 85 and higher.

Women

Table 2 presents the survival probabilities derived from the Weibull and Gompertz distributions for women aged 52 in 1992. The comparison of the survivor functions from these two distributions is similar to the male cohort (shown in Figure 1): the Gompertz survivor function is flatter and has lower probabilities of survival after age 95 than the Weibull function. In addition, the Weibull life expectancy of 29.9 years—shown in the first row of Table 2—is about two years more than the Gompertz life expectancy, implying a range of subjective life expectancies between 27.9 and 29.9 for this cohort.

Figure 2. Subjective Weibull Survivor Function Compared With SSA Cohort Life Tables for Men Aged 52

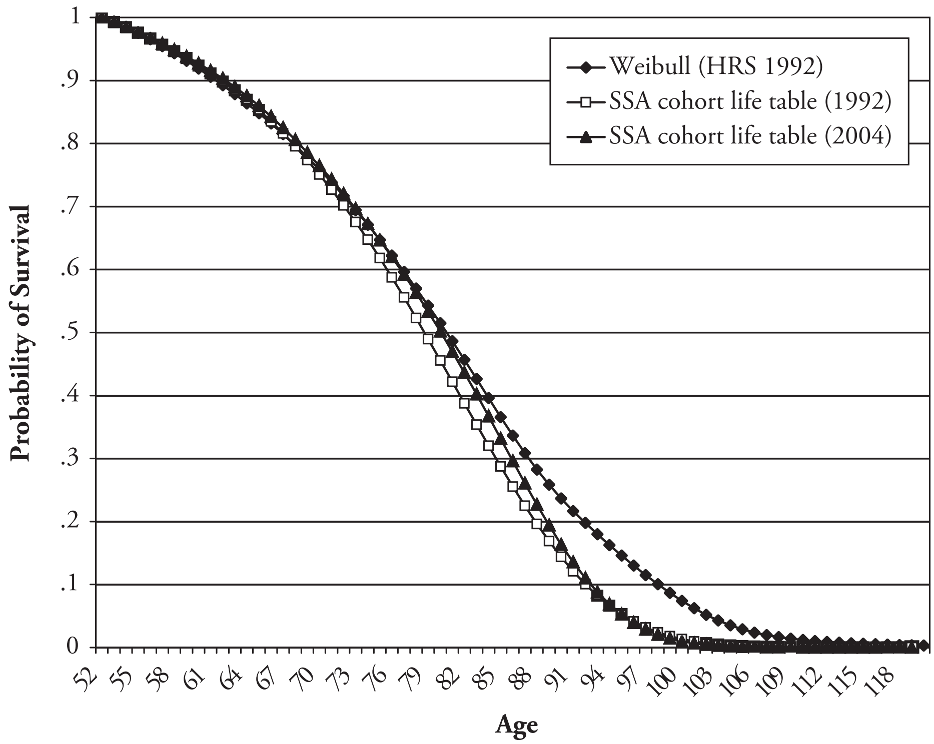


Table 2. Subjective Life Tables Versus Cohort Life Tables (SSA): Women Aged 52 in 1992

	Subjective Life Tables				1940 Cohort Life Table			
	Weibull[a]		Gompertz		Published in 1992		Published in 2004	
Age	Survival Probability S_x	Life Expectancy e_x	Survival Probability S_x	Life Expectancy e_x	Survival Probability S_x	Life Expectancy e_x	Survival Probability S_x	Life Expectancy e_x
52	1	29.9	1	27.9	1	30.9	1	30.4
55	0.979	27.5	0.946	26.4	0.986	28.3	0.986	27.8
65	0.876	20.1	0.783	20.9	0.909	20.3	0.911	19.7
75	0.696	13.9	0.621	15.0	0.747	13.5	0.752	12.7
85	0.411	9.9	0.427	9.5	0.487	7.8	0.47	7.0
95	0.178	6.8	0.193	4.8	0.153	4.2	0.118	3.5
105	0.038	6.1	0.015	1.7	0.011	2.5	0.005	2.0
115	0.008	6.2	0	1.2	0	1.3	0	1.1

[a]Weibull survivor functions are truncated at age 127 (i.e., $q_{127} = 1$). The truncation does not significantly affect life expectancy estimates before age 105.

That said, the subjective life expectancies for women and men in this cohort compare very differently with the SSA life tables. Although the subjective life expectancies for men are higher than the SSA life tables, the subjective life expectancies for women in this cohort are a good bit lower. The columns to the right in Table 2 show that according to the SSA life tables published in 1992, the life expectancy for women in this cohort was 30.9 years—about 1–3 years higher than the subjective life expectancies. Therefore, the subjective expectations from 1992 suggest that the SSA life expectancies from 1992 were too high. Remarkably, in 2004, the SSA revised *downward* its estimate of female life expectancy for this cohort to 30.4 years—a downward revision of one-half year. As shown in Figure 3, the Weibull survivor function looks quite different from the life-table survivor functions, with lower probabilities of survival at younger ages and higher probabilities of survival for the oldest-old. It is interesting to note that the reductions in life expectancy between the 1992 and 2004 SSA life-table estimates largely reflect reductions in survival probabilities among those 85 and older. In contrast, the lower life expectancy implied by the Weibull stems from lower survival probabilities through about age 90.

The Gender Gap

Although the functional forms given by the Weibull and the Gompertz are important for determining the sequence of survival probabilities, the general results hold even when looking at the raw, weighted responses to the expectations questions. Tables 3 and 4 show the weighted means of the actual survey responses of P_{75} and P_{85} for men and women aged 52 and 57 in 1992. These figures differ a bit from the predicted values based on the fitted

Figure 3. Subjective Weibull Survivor Function Compared With SSA Cohort Life Tables for Women Aged 52

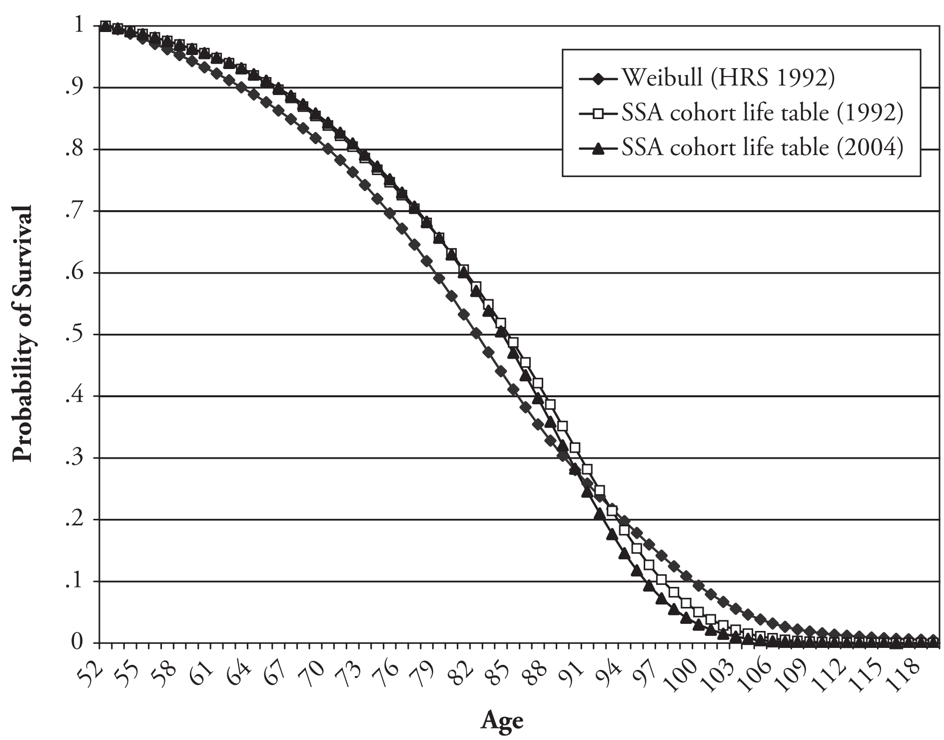


Table 3. Means of P_{75} and P_{85}, Men[a] (standard errors in parentheses)

	Age 52 in 1992			Age 57 in 1992		
	Subjective Expectation (n = 395)	Life Table 1992: 1940 Cohort	Life Table 2004: 1940 Cohort	Subjective Expectation (n = 391)	Life Table 1992: 1935 Cohort	Life Table 2004: 1935 Cohort
P_{75}	0.635 (0.015)	0.618	0.646	0.618 (0.015)	0.633	0.657
P_{85}	0.377 (0.015)	0.287	0.332	0.366 (0.015)	0.288	0.327
Life Expectancy	—	25.9	26.7	—	21.6	22.2
Life Expectancy From Fitted Weibull	28.2	26.9	28.2	23.2	22.5	23.5
Life Expectancy From Fitted Gompertz	26.5	25.6	26.9	21.8	21.4	22.4
Life Expectancy, Weibull + SSA Tilted Tail	27.0			21.9		

[a]Weighted by respondent-level weights.

Table 4. Means of P_{75} and P_{85}, Women[a] (standard errors in parentheses)

	Age 52 in 1992			Age 57 in 1992		
	Subjective Expectation (n = 472)	Life Table 1992: 1940 Cohort	Life Table 2004: 1940 Cohort	Subjective Expectation (n = 415)	Life Table 1992: 1935 Cohort	Life Table 2004: 1935 Cohort
P_{75}	0.678 (0.013)	0.747	0.752	0.653 (0.015)	0.761	0.764
P_{85}	0.428 (0.014)	0.487	0.47	0.43 (0.015)	0.489	0.468
Life Expectancy	—	30.9	30.4	—	26.4	25.8
Life Expectancy From Fitted Weibull	29.9	32.5	32.1	24.8	27.9	27.4
Life Expectancy From Fitted Gompertz	27.9	31.2	30.8	23.7	26.6	26.1
Life Expectancy, Weibull + SSA Tilted Tail	29.0			23.9		

[a]Weighted by respondent-level weights.

Weibull and Gompertz survivor functions presented in Tables 1 and 2 but yield the same basic conclusions. That is, men in both age groups had much higher estimates of their probability of surviving to age 85 than indicated in the life tables published in 1992. And upward revisions to the SSA life-table probabilities for men in 2004 resulted in a 50% reduction in the difference between SSA estimates and the subjective estimates of the probability of living to age 85.

Meanwhile, women reported subjective probabilities of survival that were lower than the life tables by a good margin for both P_{75} and P_{85}. In this case, the life-table probability of living to 75 was revised upward slightly between 1992 and 2004, and the probability of living to 85 and beyond was revised downward. Taken together, the life expectancy for

Table 5. Differences in Life Expectancy by Gender: Female Life Expectancy Less Male Life Expectancy

	Age 52	Age 57
Cohort Life Table, 1992	5.0	4.8
Cohort Life Table, 2004	3.7	3.6
Percentage Change	–26	–25
Subjective Expectations (Weibull)	1.7	1.6
Memo		
Cohort life table 1992, fitted Weibull	5.6	5.4
Cohort life table 2004, fitted Weibull	3.9	3.9
Percentage change	–30	–28
Cohort life table 1992, fitted Gompertz	5.6	5.2
Cohort life table 2004, fitted Gompertz	3.9	3.7
Percentage change	–30	–29

women in both cohorts was revised downward one-half year in each cohort, moving the life-table estimate closer to the subjective life expectancy estimates.

These results for men and women indicate that the gender difference in mortality risk was perceived in 1992 to be declining faster than predicted by the SSA at that time. As shown in Table 5, the life tables from 1992 predicted that the difference between female and male life expectancy was about 5 years for both cohorts. By 2004, revisions to the male and female life tables for these cohorts reduced the gender gap to about 3.7 years—a 25% downward revision in just over one decade. The lower panel of Table 5 shows that the implied longevity difference from the subjective life tables, which is about 1.7 years, is still quite a bit lower than the 2004 life-table estimates. These expectations suggest that the mortality difference between men and women in these cohorts could narrow even further.

The bottom line is that the subjective, cohort life tables, which are based only on data collected in 1992, foreshadowed revisions to the SSA cohort life tables between 1992 and 2004. These included upward revisions to male life expectancy and downward revisions to female life expectancy, implying a narrowing of the gender gap.

However, one might argue that for various reasons, women might systematically understate their probabilities of survival relative to men. For example, if women have higher morbidity or greater risk aversion relative to men, they may understate their probabilities of survival relative to men. Indeed, there is evidence that disability prevalence is higher for elderly women than for elderly men (see, e.g., Leveille et al. 2000). If women incorrectly infer that their higher rates of disability lead to higher mortality rates, the difference in longevity between men and women as measured by subjective expectations would always understate the true gender gap in mortality risk. To explore this possibility, I compare the first 8 years of the estimated subjective survival probabilities with the actual mortality experience of the HRS cohort to see whether women tended to have lower estimated survival probabilities relative to actual survival outcomes than their male counterparts.[13] This exercise is complicated a bit by the fact that survival status is not always known for respondents who exit the sample. To account for this uncertainty, I calculate an upper and a lower bound

13. For convenience, I refer to those between the ages of 51 and 61, inclusive, at the time of the initial interview as the "HRS cohort" although technically, the HRS is representative of those born between 1931 and 1941 (and their spouses) and includes some 50- and 62-year-olds as well.

for the actual survival probabilities in the sample by making alternative assumptions about survival status when it is unknown. The upper bound is calculated by assuming that those for whom survival status is unknown died at the same rate as those for whom survival status is known; the lower bound assumes that all those for whom survival status is unknown died upon exiting the sample. It is likely that the true survival probabilities of the cohort lie within these bounds, which together with the subjective survivor functions, are estimated for the entire cohort of men and women between ages 51 and 61, inclusive.

As shown in Figure 4, the estimated survivor functions for the male cohort predict actual experience in the cohort fairly well, with the initial probabilities being a bit low. Further out, however, the subjective probabilities lie close to midpoint between the upper and lower bounds of the actual survival probabilities realized by the cohort. Comparatively, as shown in Figure 5, women do not do as well: the subjective survivor functions for women understate the initial survival probabilities by a good bit more earlier in the period. Although they lie between the bounds of actual experience later on, they are much closer to the lower bound of the actual survival probabilities than are the men. These plots suggest that subjective survivor functions estimated for women understate survival probabilities relative to actual survival probabilities, whereas the survivor functions estimated for men appear to do a better job. However, given the limited number of years of actual survival experience of the cohort, it is difficult to know whether these fairly small differences in optimism, if you will, translate into large differences in life expectancy overall.

The flatter Weibull estimates for the women imply lower initial survival probabilities, but the fatter tails of the Weibull likely imply higher survival probabilities at advanced ages. As a result, it is not clear how one would adjust subjective life tables to uncover the correct prediction for the gender gap implied by the subjective expectations data. Further

Figure 4. Subjective Survivor Function Versus Actual Mortality Experience for Men Aged 51–61

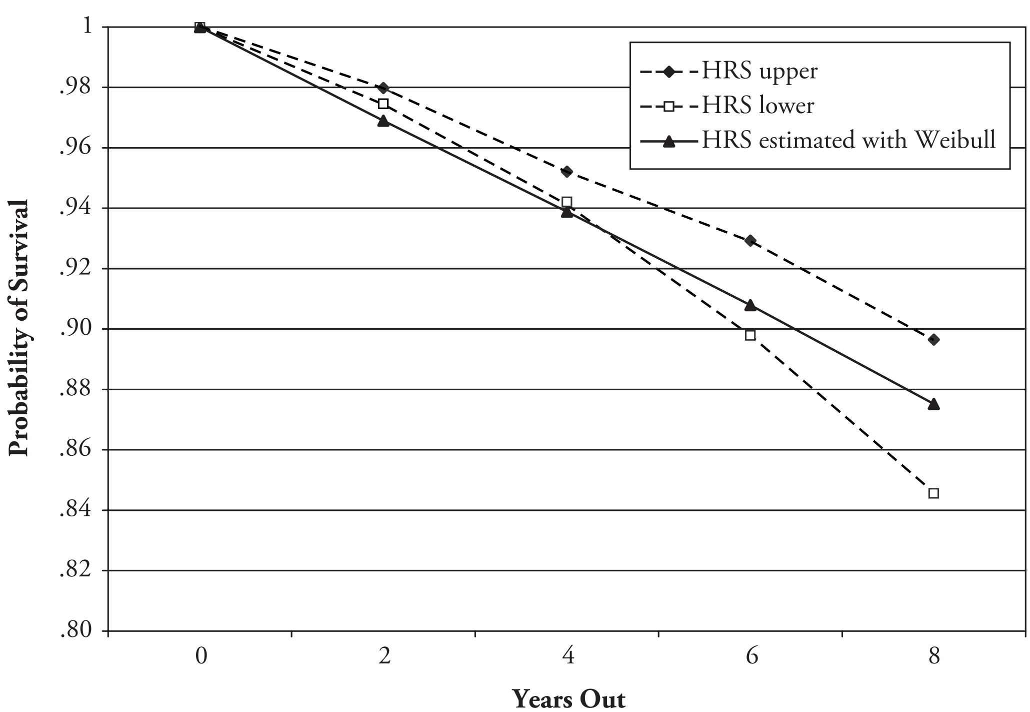
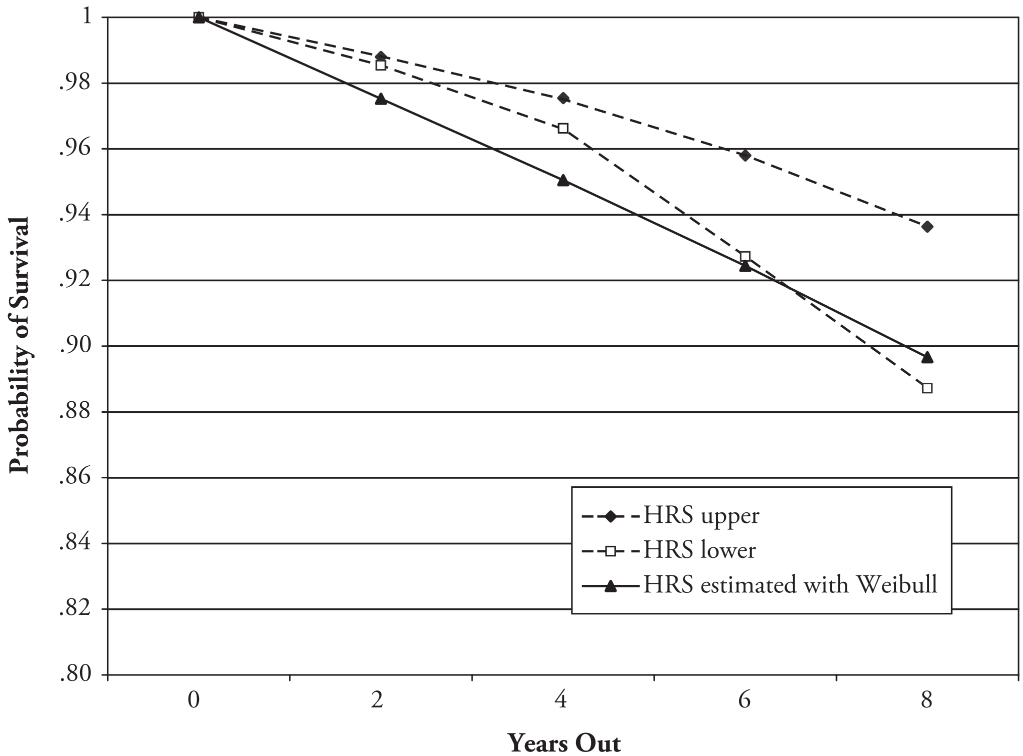


Figure 5. Subjective Survivor Functions Versus Actual Mortality Experience for Women Aged 51–61



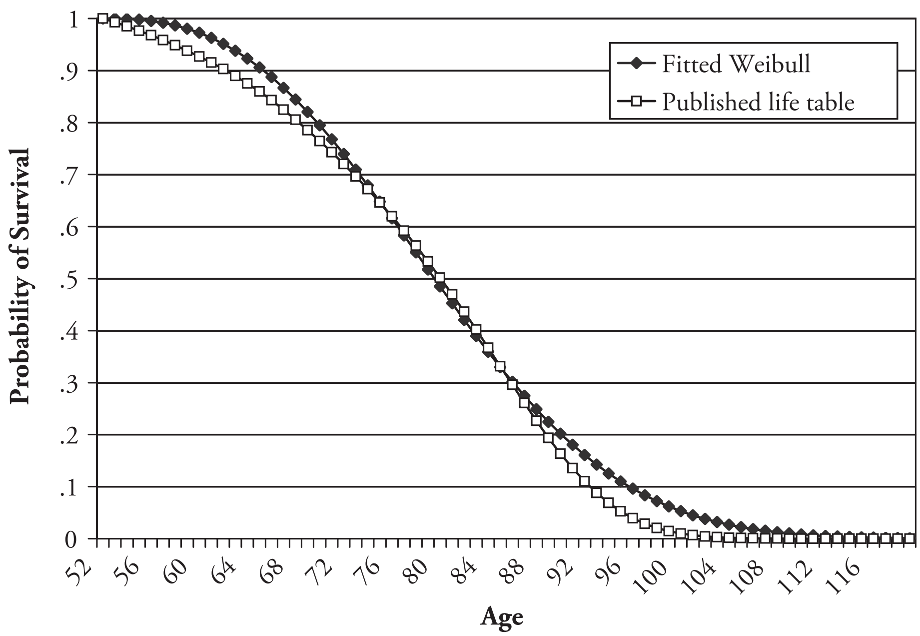
research is needed to determine the factors that underlie the apparent propensity of women to overestimate their mortality risk.

Functional Form Assumptions

A key assumption in this analysis is that the Weibull survivor function fitted through three points on the subjective survivor function can yield a meaningful sequence of survival probabilities for each person in the HRS sample. In an ideal world, one would not have to resort to functional form assumptions: respondents would report all points on the subjective survivor function (or substantially all), and one could estimate the subjective survivor function nonparametrically. Unfortunately, I have only two points to work with prior to age 85. As a result, the behavior of the subjective survivor function beyond age 85 is completely determined by functional form assumptions. In particular, the Weibull, as noted earlier, appears to yield higher probabilities of living beyond age 95 even when the estimated life expectancy is lower than the life-table estimates—for example, for the women whose data appear in Table 4.

This section explores the sensitivity of the main results of the paper to assuming a Weibull functional form for the subjective survivor functions. To do this, I conduct two separate sensitivity tests. First, I transform the SSA cohort life tables to the same basis as the subjective life tables by using the same estimation method to provide a Weibull approximation to the SSA survivor functions. Second, I provide an alternative estimate of the right tail of the Weibull by using the SSA life-table probabilities to "tilt" the subjective probabilities beyond age 85 according to the following formula:

Figure 6. Fitted Weibull Versus Published Life Table: SSA 1940 Male Cohort (2004)



$$P(t \mid age) = \underbrace{P(t \mid 85, age)}_{\textit{SSA life table}} \times \underbrace{P(85 \mid age)}_{\textit{HRS}}.$$

This gives the subjective survivor functions the same shape as the SSA life tables after age 85, allowing me to explore the effect of the right tail on the main results of this paper.

Weibull Approximation to SSA Cohort Life Tables

As noted earlier, one might argue that the Weibull is not flexible enough to capture the shape of the human survivor function; in particular, the fat right tail associated with the Weibull is inappropriate and may be driving the results described earlier in this paper. To explore the importance of functional form assumptions, I fit Weibull functional forms to the SSA cohort life tables from 1992 and 2004, using the same three points of the survivor function used in the subjective life tables: namely, P_{75}, P_{85}, and P_{110}. Figure 6 shows that for men, the Weibull functional form predicts higher survival probabilities both before age 75 and after age 90 than the life-table probabilities.[14] As a result, life expectancies derived from these Weibull estimates are higher; indeed, as shown at the bottom of Table 3, male life expectancies are roughly 1–1.5 years higher than those computed by SSA. However, this transformation, in effect, makes the life-table probabilities more directly comparable with the subjective life tables, and the results are somewhat reassuring. The subjective life expectancy was still quite a bit higher (1.25 years) than the fitted Weibull life-table life expectancy from 1992 but matched the fitted Weibull life-table estimate for 2004. Thus, the main result still holds: subjective life expectancies from 1992 predicted an upward revision to male life expectancies between 1992 and 2004.[15, 16]

14. This is also true for the older 1935 male cohort.

15. The same basic result obtains for men age 57 in 1992.

16. For reference, the SSA life-table probabilities were also fitted to the Gompertz functional form, shown in the last row of Table 3. The Gompertz, which does a much better job of fitting the right tail of the survivor func-

The results for women shown in Table 4 are similar. In this case, however, the SSA life-expectancy estimates from both the fitted Weibull and Gompertz are higher than the subjective life expectancies calculated for each cohort. Nevertheless, the main result holds: SSA-fitted life expectancies were revised downward about the same amount as the actual life expectancies, and the subjective life expectancy is still lower than both the actual and fitted SSA life-table estimates from 2004.

The memo items in Table 5 show that the diminution of the gender gap in longevity is highly stable across the different fitted and actual life-expectancy values. Although the fitted life-table estimates of the gap are slightly higher than the actual, the percentage reduction from 1992 to 2004 is 30%—roughly the same as the actual reduction between the 1992 and the 2004 life tables.

Tilted Subjective Life Tables

The exercise that I described earlier demonstrates that despite a level effect in the life expectancies generated from the Weibull, the relationship between the gender-specific subjective expectations of survival and those implied by the SSA cohort remains stable. This section explores whether the results are sensitive to transforming the tail of the Weibull subjective cohort-survivor function to conform to the shape of the SSA cohort-survivor function. Hereafter, I refer to this hybrid Weibull plus SSA life-table tail as the "tilted Weibull."

As I noted earlier, the tails of the Weibull survivor functions are tilted according to the following formula:

$$P_i(t \mid age_i) = \underbrace{P_x(t \mid 85, age_i)}_{\text{SSA life table}} \times \underbrace{P_i(85 \mid age_i)}_{\text{HRS}},$$

where $t > 85$. The summary results from this calculation are shown in the last rows of Tables 3 and 4. The life expectancies for men and women derived from the tilted Weibull are around 1 year less than the fitted Weibull. For men, though, these life expectancies are still greater than the 1992 cohort life tables; and for women, they are still less. In all cases, the estimates of life expectancy from the tilted Weibull lie between the Gompertz lower bound and the Weibull upper bound. The estimates imply a gender gap of about 2 years—a bit higher than the gap implied by the fitted Weibull.

The conclusion from these sensitivity analyses is that while one should not place too much emphasis on the precise level of the derived life expectancy estimates, the Gompertz and the Weibull probably provide informative lower and upper bounds, respectively, to the subjective life expectancies. Moreover, these analyses suggest that the main qualitative results regarding the relationship between gender-specific subjective survivor functions and those published by SSA is fairly robust to alternative functional form assumptions.

CONCLUDING REMARKS

The Weibull and the Gompertz functional forms differ dramatically in their implications regarding mortality risk at very old ages, with the Weibull implying higher rates of survival for the oldest-old than the Gompertz. Because the 1940 and 1935 cohorts have only just recently (in 2005) reached the ages 65 and 70, respectively, their mortality experience at the oldest ages has not yet been realized. Moreover, there is a wide range of opinion about the pace of future mortality improvements at very advanced ages. In one camp are those who believe that the pace of future improvements will slow because we are nearing a biological limit to human life expectancy (Olshansky and Carnes 2001). In the other camp are those who believe that we have not yet come close to the biological limit of human life

tion, implies a lower life expectancy than the Weibull, which is closer to the actual life-table life expectancies. Like with the Weibull, the basic results described herein continue to hold.

expectancy (see, e.g., Oeppen and Vaupel 2002).[17] What is not disputed is that past forecasts of mortality improvements have been far too conservative (Oeppen and Vaupel 2002) and that assumptions about future old-age mortality are vital to estimating the expected longevity of current and future cohorts.

Old-age mortality is very difficult to predict because it requires not only an understanding of the process of senescence—which is influenced by genetic, environmental, and behavioral factors—but also a prediction of medical advances as well as other important environmental variables. In this paper, I suggest that individuals have a unique understanding of their own individual aging processes, conditional upon private information, which could include knowledge of their genetic background as well as environmental and behavioral risk factors. Given this private information, individuals form expectations about future survival probabilities that may provide additional information to demographers and policymakers in their challenge to predict mortality. I find that expectations elicited in 1992 predicted the unusual direction of revisions to U.S. life expectancy by gender between 1992 and 2004; that is, male life expectancy was revised upward, and female life expectancy was revised downward. The subjective expectations of women suggest that female life expectancies produced by the SSA might still be on the high side, and that subjective life expectancies for men appear to be roughly in line with the 2004 life tables. That said, it is important to emphasize the qualitative over the quantitative aspects of this study because it appears that women tend to overstate their mortality risk relative to men. Further research is necessary to determine why women overestimate mortality risk relative to men as well as what implications this might have for the use subjective survival probabilities to predict mortality risk.

APPENDIX A

Because of the form of the survivor function, the Weibull parameters are undefined for persons who report $P_{75} = P_{85}$. However, a respondent who reports P_{75} close to P_{85} may be conveying valuable information regarding the perceived flatness of the subjective survivor function, and it would be unfortunate to be forced to exclude such a large and potentially interesting segment of the sample. The format of the expectation questions in the first wave of the HRS requires respondents to round survival probabilities to the nearest tenth. As a result, it is reasonable to assume that the "true" expectation lies in some interval around $P_{75} = P_{85}$: that is, $P_{75} \in [P_{75} - .05, P_{75} + .05]$ and $P_{78} \in [P_{75} - .05, P_{85} + .05]$. Hence, to retain nearly one-third of the sample who report $P_{75} = P_{85}$, I reassign the probability of living to 75 equal to the upper bound of the interval (P_{75} + .05) and also set the probability of living to 85 to the lower bound of the interval (P_{75} – .05). For example, a person who reported $P_{75} = P_{85} = .5$ would be reassigned $P_{75} = .55$ and $P_{85} = .45$. This assignment rule imposes the maximum distance allowed within the interval, thereby implying more credible Weibull estimates.

In addition, in order to estimate the Weibull, probabilities of 0 and 1 are reassigned .01 and .99, respectively. If $P_{75} = P_{85} = .99$, then P_{85} is set to .95; and if $P_{75} = P_{85} = .01$, then P_{75} is set to .05.

To check the robustness of the results to these assumptions, I start with the unadjusted reported survival probabilities and follow the same procedure for constructing subjective survivor functions.[18] Of the 472 women aged 52 in 1992, 137—about 30%—reported $P_{75} = P_{85}$. Of that group, one-third reported both probabilities equal to 1, one-fifth reported both probabilities equal to 0, and one-fifth reported both probabilities equal to 0.5. The life

17. For example, estimates from a risk-factor simulation model developed by Manton, Stallard, and Tolley (1991) suggest that life expectancy at birth could be dramatically higher than the U.S. life tables currently predict.

18. All adjustments were removed except for the cases in which $P_{75} = P_{85} = 0$, which cannot be estimated via the Weibull without some adjustment.

expectancies derived from the unadjusted survival probabilities are generally higher than the adjusted life expectancies, particularly where the probabilities of living to 75 and 85 are close to or equal to 1. For example, if reported probabilities of living to 75 and 85 are both equal to 1, the unadjusted Weibull life expectancy is 10.5 years higher than the adjusted life expectancy for 52-year-olds (54.7 years vs. 44.2 years).

In the aggregate, the unadjusted subjective life expectancies for the 1940 cohort were about 1 year higher for both men and women than the adjusted life expectancies, bringing the women more in line with the SSA life tables while exacerbating the difference for men and leaving the gender gap about unchanged. Therefore, these results would still predict a narrowing of the gender gap, although they would suggest that men will live even longer than reported in this paper, relative to the SSA life tables.

Although the path of the survival probabilities generated by the unadjusted variables is fairly similar to that derived from the adjusted probabilities through about age 95, the unadjusted probabilities of survival are much higher between ages 95 and 110 before dropping down because of the higher life expectancies and lower variances estimated for those optimistic respondents who reported that they were certain to live to age 85. The unusually high probabilities of survival at these ages lead me to favor the adjusted life-table estimates reported in this paper. The problems with estimating these survivor functions point to the importance of understanding mortality rates among the oldest-old, for which I have no subjective data in the HRS beyond age 85. For future work in this area, it would be useful to have another point on the subjective survivor function to work with, perhaps the probability of surviving to age 95.

REFERENCES

Bassett, W. and R. Lumsdaine. 2001."Probability Limits—Are Subjective Assessments Adequately Accurate?" *Journal of Human Resources* 36:327–63.

Bell, F., A. Wade, and S. Goss. 1992. "Life Tables for the United States Social Security Area 1900–2080." Actuarial Study No. 107, U.S. Department of Health and Human Services, Social Security Administration, Office of the Actuary.

Bernheim, B.D. 1989. "The Timing of Retirement: A Comparison of Expectations and Realizations." Pp. 335–55 in *The Economics of Aging,* edited by D. Wise. Chicago: The University of Chicago Press.

———. 1990. "How do the Elderly Form Expectations: An Analysis of Responses to New Information." Pp. 259–83 in *Issues in the Economics of Aging,* edited by D. Wise. Chicago: The University of Chicago Press.

Cutler, D. and E. Meara. 2004. "Changes in the Age Distribution of Mortality Over the Twentieth Century." Pp. 333–65 in *Perspectives on the Economics of Aging,* edited by D. Wise. Chicago: The University of Chicago Press.

Dominitz, J. 1998. "Earnings Expectations, Revisions, and Realizations." *The Review of Economics and Statistics* 80:374–88.

Dominitz, J. and C. Manski. 1997. "Using Expectations Data to Study Subjective Income Expectations." *Journal of the American Statistical Association* 2:855–62.

Economos, A. 1982. "Rate of Aging, Rate of Dying, and the Mechanism of Mortality." *Archives of Gerontological Geriatrics* 1:3–27.

Gan, L., M. Hurd, and D. McFadden. 2003. "Individual Subjective Survival Curves." NBER Working Paper 9480. National Bureau of Economic Research, Cambridge, MA.

Hamermesh, D. 1985. "Expectations, Life Expectancy, and Economic Behavior." *Quarterly Journal of Economics* 100(2):389–408.

Hurd, M. and K. McGarry. 1995. "Evaluation of the Subjective Probabilities of Survival in the Health and Retirement Study." *Journal of Human Resources* 30(Suppl.):S268–S292.

———. 2002. "The Predictive Validity of Subjective Probabilities of Survival." *The Economic Journal* 112:966–85.

Juster, F.T. and R. Suzman. 1995. "An Overview of the Health and Retirement Study." *Journal of Human Resources* 30(Suppl.):S7–S56.

Lawless, J.F. 1982. *Statistical Models and Methods for Lifetime Data*. New York: John Wiley & Sons.

Lee, R. 2003. "The Demographic Transition: Three Centuries of Fundamental Change." *Journal of Economic Perspectives* 17(4):167–90.

Leveille, S.G., B.W.J.H. Penninx, D. Melzer, G. Izmirlian, and J.M. Guralnik, 2000. "Sex Differences in the Prevalence of Mobility Disability in Old Age: The Dynamics of Incidence, Recovery, and Mortality." *Journal of Gerontology: Social Sciences* 55B(1):S41–S50.

Manski, C. 1990. "The Use of Intentions Data to Predict Behavior: A Best Case Analysis." *Journal of the American Statistical Association* 85:934–40.

———. 2004. "Measuring Expectations" *Econometrica* 72:1329–76.

Manton, K.G., E. Stallard, and H.D. Tolley. 1991. "Limits to Human Life Expectancy: Evidence, Prospects, and Implications." *Population and Development Review* 17:603–37.

National Center for Health Statistics (NCHS). 2004. "Health, United States, 2004." Hyattsville, MD: NCHS. Available online at http://www.cdc.gov/nchs/hus.htm

Oeppen, J. and J. Vaupel. 2002. "Broken Limits to Life Expectancy," *Science* 296:1029–31.

Olshansky, S.J. and B.A. Carnes. 2001. *The Quest for Immortality: Science at the Frontiers of Aging*. New York: W.W. Norton and Co.

Pollard, A.H., F. Yusuf, and G.N. Pollard. 1990. *Demographic Techniques*. New York: Pergamon Press.

Vaupel, J., A. Baudisch, M. Dolling, D. Roach, and J. Gampe. 2004."The Case for Negative Senescence." MPIDR Working Paper 2004-02. Max Planck Institute for Demographic Research, Rostock, Germany.

Vaupel, J. and H. Lundstrom. 1994. "Longer Life Expectancy? Evidence From Sweden of Reductions in Mortality Rates at Advanced Ages." Pp. 79–94 in *Studies in the Economics of Aging,* edited by D. Wise. Chicago: The University of Chicago Press.

Wilson, D. 1994. "The Analysis of Survival (Mortality) Data: Fitting Gompertz, Weibull and Logistic Functions." *Mechanisms of Ageing and Development* 74(1994):15–33.